sklearn.neighbors.KNeighborsClassifier

» *class* `sklearn.neighbors.KNeighborsClassifier`(*n_neighbors=5*, *weights='uniform'*, *algorithm='auto'*, *leaf_size=30*, *p=2*, *metric='minkowski'*, *metric_params=None*, *n_jobs=1*, ***kwargs*) [source]

Classifier implementing the k-nearest neighbors vote.

Read more in the User Guide.

Parameters: **n_neighbors** : int, optional (default = 5)

Number of neighbors to use by default for `k_neighbors` queries.

weights : str or callable

weight function used in prediction. Possible values:

- 'uniform' : uniform weights. All points in each neighborhood are weighted equally.
- 'distance' : weight points by the inverse of their distance. in this case, closer neighbors of a query point will have a greater influence than neighbors which are further away.
- [callable] : a user-defined function which accepts an array of distances, and returns an array of the same shape containing the weights.

Uniform weights are used by default.

algorithm : {'auto', 'ball_tree', 'kd_tree', 'brute'}, optional

Algorithm used to compute the nearest neighbors:

- 'ball_tree' will use `BallTree`
- 'kd_tree' will use `KDTree`
- 'brute' will use a brute-force search.
- 'auto' will attempt to decide the most appropriate algorithm based on the values passed to `fit` method.

Note: fitting on sparse input will override the setting of this parameter, using brute force.

leaf_size : int, optional (default = 30)

Leaf size passed to BallTree or KDTree. This can affect the speed of the construction and query, as well as the memory required to store the tree.

The optimal value depends on the nature of the problem.

metric : string or DistanceMetric object (default = 'minkowski')

the distance metric to use for the tree. The default metric is minkowski, and with p=2 is equivalent to the standard Euclidean metric. See the documentation of the DistanceMetric class for a list of available metrics.

p : integer, optional (default = 2)

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Power parameter for the Minkowski metric. When p = 1, this is equivalent to using manhattan_distance (l1), and euclidean_distance (l2) for p = 2. For arbitrary p, minkowski_distance (l_p) is used.

metric_params : dict, optional (default = None)

Additional keyword arguments for the metric function.

n_jobs : int, optional (default = 1)

The number of parallel jobs to run for neighbors search. If `-1`, then the number of jobs is set to the number of CPU cores. Doesn't affect `fit` method.

See also: `RadiusNeighborsClassifier`, `KNeighborsRegressor`, `RadiusNeighborsRegressor`, `NearestNeighbors`

Notes

See Nearest Neighbors in the online documentation for a discussion of the choice of `algorithm` and `leaf_size`.

Warning: Regarding the Nearest Neighbors algorithms, if it is found that two neighbors, neighbor *k+1* and *k*, have identical distances but but different labels, the results will depend on the ordering of the training data.

http://en.wikipedia.org/wiki/K-nearest_neighbor_algorithm

Examples

```
>>> X = [[0], [1], [2], [3]]
>>> y = [0, 0, 1, 1]
>>> from sklearn.neighbors import KNeighborsClassifier
>>> neigh = KNeighborsClassifier(n_neighbors=3)
>>> neigh.fit(X, y)
KNeighborsClassifier(...)
>>> print(neigh.predict([[1.1]]))
[0]
>>> print(neigh.predict_proba([[0.9]]))
[[ 0.66666667  0.33333333]]
```

>>>

Methods

`fit`(X, y)	Fit the model using X as training data and y as target values
`get_params`([deep])	Get parameters for this estimator.
`kneighbors`([X, n_neighbors, return_distance])	Finds the K-neighbors of a point.
`kneighbors_graph`([X, n_neighbors, mode])	Computes the (weighted) graph of k-Neighbors for points in X
`predict`(X)	Predict the class labels for the provided data
`predict_proba`(X)	Return probability estimates for the test data X.
`score`(X, y[, sample_weight])	Returns the mean accuracy on the given test data and labels.
`set_params`(**params)	Set the parameters of this estimator.

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`__init__`(*n_neighbors=5*, *weights='uniform'*, *algorithm='auto'*, *leaf_size=30*, *p=2*, *metric='minkowski'*, *metric_params=None*, *n_jobs=1*, ***kwargs*) [source]

`fit`(*X*, *y*) [source]

Fit the model using X as training data and y as target values

Parameters: **X** : {array-like, sparse matrix, BallTree, KDTree}

Training data. If array or matrix, shape [n_samples, n_features], or [n_samples, n_samples] if metric='precomputed'.

y : {array-like, sparse matrix}

Target values of shape = [n_samples] or [n_samples, n_outputs]

`get_params`(*deep=True*) [source]

Get parameters for this estimator.

Parameters: **deep: boolean, optional** :

If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns: **params** : mapping of string to any

Parameter names mapped to their values.

`kneighbors`(*X=None*, *n_neighbors=None*, *return_distance=True*) [source]

Finds the K-neighbors of a point.

Returns indices of and distances to the neighbors of each point.

Parameters:	**X** : array-like, shape (n_query, n_features), or (n_query, n_indexed) if metric == 'precomputed' The query point or points. If not provided, neighbors of each indexed point are returned. In this case, the query point is not considered its own neighbor. **n_neighbors** : int Number of neighbors to get (default is the value passed to the constructor). **return_distance** : boolean, optional. Defaults to True. If False, distances will not be returned
Returns:	**dist** : array Array representing the lengths to points, only present if return_distance=True **ind** : array Indices of the nearest points in the population matrix.

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Examples

In the following example, we construct a NeighborsClassifier class from an array representing our data set and ask who's the closest point to [1,1,1]

```
>>> samples = [[0., 0., 0.], [0., .5, 0.], [1., 1., .5]]
>>> from sklearn.neighbors import NearestNeighbors
>>> neigh = NearestNeighbors(n_neighbors=1)
>>> neigh.fit(samples)
NearestNeighbors(algorithm='auto', leaf_size=30, ...)
>>> print(neigh.kneighbors([[1., 1., 1.]]))
(array([[ 0.5]]), array([[2]]...))
```

As you can see, it returns [[0.5]], and [[2]], which means that the element is at distance 0.5 and is the third element of samples (indexes start at 0). You can also query for multiple points:

```
>>> X = [[0., 1., 0.], [1., 0., 1.]]
>>> neigh.kneighbors(X, return_distance=False)
array([[1],
       [2]]...)
```

kneighbors_graph(*X=None*, *n_neighbors=None*, *mode='connectivity'*) [source]

Computes the (weighted) graph of k-Neighbors for points in X

Parameters: **X** : array-like, shape (n_query, n_features), or (n_query, n_indexed) if metric == 'precomputed'

The query point or points. If not provided, neighbors of each indexed point are returned. In this case, the query point is not considered its own neighbor.

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n_neighbors : int

Number of neighbors for each sample. (default is value passed to the constructor).

mode : {'connectivity', 'distance'}, optional

Type of returned matrix: 'connectivity' will return the connectivity matrix with ones and zeros, in 'distance' the edges are Euclidean distance between points.

Returns: **A** : sparse matrix in CSR format, shape = [n_samples, n_samples_fit]

n_samples_fit is the number of samples in the fitted data A[i, j] is assigned the weight of edge that connects i to j.

See also: `NearestNeighbors.radius_neighbors_graph`

Examples

```
>>> X = [[0], [3], [1]]
>>> from sklearn.neighbors import NearestNeighbors
>>> neigh = NearestNeighbors(n_neighbors=2)
>>> neigh.fit(X)
NearestNeighbors(algorithm='auto', leaf_size=30, ...)
>>> A = neigh.kneighbors_graph(X)
>>> A.toarray()
array([[ 1.,  0.,  1.],
       [ 0.,  1.,  1.],
       [ 1.,  0.,  1.]])
```

`predict`(*X*) [source]

Predict the class labels for the provided data

Parameters: **X** : array-like, shape (n_query, n_features), or (n_query, n_indexed) if metric == 'precomputed'

Test samples.

Returns: **y** : array of shape [n_samples] or [n_samples, n_outputs]

Class labels for each data sample.

predict_proba(*X*) [source]

Return probability estimates for the test data X.

Parameters: **X** : array-like, shape (n_query, n_features), or (n_query, n_indexed) if metric == 'precomputed'

Test samples.

Returns: **p** : array of shape = [n_samples, n_classes], or a list of n_outputs

of such arrays if n_outputs > 1. The class probabilities of the input samples. Classes are ordered by lexicographic order.

score(*X*, *y*, *sample_weight=None*) [source]

Returns the mean accuracy on the given test data and labels.

In multi-label classification, this is the subset accuracy which is a harsh metric since you require for each sample that each label set be correctly predicted.

Parameters: **X** : array-like, shape = (n_samples, n_features)

Test samples.

y : array-like, shape = (n_samples) or (n_samples, n_outputs)

True labels for X.

sample_weight : array-like, shape = [n_samples], optional

Sample weights.

Returns: **score** : float

Mean accuracy of self.predict(X) wrt. y.

set_params(***params*) [source]

Set the parameters of this estimator.

The method works on simple estimators as well as on nested objects (such as pipelines). The former have parameters of the form `<component>__<parameter>` so that it's possible to update each component of a nested object.

Returns: **self** :

Examples using `sklearn.neighbors.KNeighborsClassifier`

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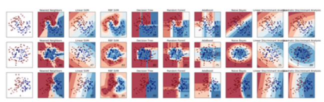
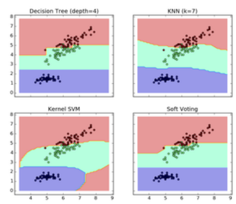


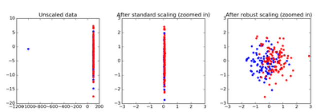
Classifier comparison



Plot the decision boundaries of a VotingClassifier

Digits Classification Exercise

Nearest Neighbors Classification



Robust Scaling on Toy Data

Classification of text documents using sparse features